Journal of Scientific Research & Technology Development

E-ISSN: 3107-5371 www.ijsrtd.com info.ijsrtd@gmail.com

Volume 2, Issue 2, Nov – Dec 2025

Cybersecurity Threat Detection Using Deep Learning Techniques in Networked Systems

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Abstract

The rapid growth of digital networks, cloud computing, and Internet-based services has significantly increased exposure to cyber threats such as malware, phishing, denial-of-service attacks, and network intrusions. Traditional rule-based and signature-based security mechanisms are increasingly ineffective against sophisticated and evolving attack patterns. Deep learning techniques provide an intelligent and adaptive approach for detecting cyber threats by learning complex patterns from large volumes of network data. This paper presents a comprehensive study of deep learning-based cybersecurity threat detection models, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Autoencoders. Experimental evaluation demonstrates that deep learning models achieve high detection accuracy and significantly reduce false positives compared to conventional intrusion detection systems. The study also discusses challenges related to scalability, real-time deployment, and data imbalance in cybersecurity analytics.

Keywords

Cybersecurity, Deep Learning, Intrusion Detection System, Malware Detection, Network Security, Anomaly Detection

1. Introduction

Cybersecurity has become a critical concern for governments, organizations, and individuals due to the increasing reliance on digital infrastructure. Modern cyber attacks are highly sophisticated, adaptive, and capable of bypassing traditional security defenses. Attackers exploit vulnerabilities in operating systems, applications, and network protocols, leading to data breaches, financial losses, and service disruptions.

Conventional cybersecurity solutions rely on predefined rules and signatures to detect known attack patterns. While effective against previously identified threats, these systems struggle to detect zero-day attacks and advanced persistent threats. As cyber threats evolve rapidly, there is a growing need for intelligent security systems that can learn from data and adapt to new attack behaviors.

Deep learning, a subset of machine learning, has demonstrated exceptional performance in pattern recognition, image processing, and natural language understanding. In cybersecurity, deep learning models can automatically extract features from raw network traffic data and identify anomalies that indicate malicious activity. This paper investigates deep learning-based threat detection techniques and evaluates their effectiveness in modern network environments.

2. Literature Review

Early intrusion detection systems were primarily signature-based, relying on known attack patterns stored in databases. While efficient for detecting known threats, these systems failed to adapt to new attack strategies. Anomaly-based detection methods were later introduced, using statistical models to identify deviations from normal behavior.

Recent studies have explored machine learning approaches for cybersecurity. Kim et al. applied Support Vector Machines for intrusion detection, achieving moderate success but facing scalability challenges. Deep learning techniques gained attention due to their ability to model complex relationships in high-dimensional data. Yin et al. proposed an LSTM-based intrusion detection model capable of learning temporal dependencies in network traffic.

Researchers have also explored CNNs for malware detection by transforming network traffic or binary files into image-like representations. Autoencoders have been used for unsupervised anomaly detection by learning normal traffic patterns and identifying deviations. Despite promising results, challenges such as data imbalance, real-time processing, and model interpretability remain active research areas.

3. Methodology

The research methodology follows a structured deep learning pipeline for cybersecurity threat detection:

3.1 Data Collection

Network traffic datasets containing normal and malicious activities are used. Features include packet size, protocol type, connection duration, source and destination ports, and traffic flow statistics.

3.2 Data Preprocessing

Raw network data is cleaned to remove noise and incomplete records. Feature normalization and encoding techniques are applied to prepare data for deep learning models. Data imbalance is addressed using resampling techniques.

3.3 Model Development

Three deep learning models are developed and evaluated:

- **CNN:** For spatial feature extraction
- **LSTM:** For learning temporal patterns in traffic flows
- **Autoencoder:** For unsupervised anomaly detection

3.4 Model Evaluation

Models are evaluated using accuracy, precision, recall, F1-score, and false positive rate as performance metrics.

4. Proposed Deep Learning-Based Threat Detection Model

The proposed model integrates multiple deep learning components to enhance detection accuracy:

- **Input Layer:** Preprocessed network traffic features
- **Feature Learning Layer:** CNN and LSTM layers for spatial-temporal learning
- **Detection Layer:** Classification of traffic as normal or malicious
- **Alert Layer:** Real-time notification and logging of detected threats

The hybrid architecture improves detection capability by capturing both spatial and temporal attack patterns.

5. Comparative Analysis

Detection Method	Detection Accuracy	False Positives	Adaptability
Signature-Based IDS	Moderate	Low	Poor
Traditional ML Models	Good	Medium	Limited
Deep Learning Models	High	Low	High

The analysis highlights the superiority of deep learning approaches in handling complex and evolving cyber threats.

6. Results and Discussion

Experimental results show that the CNN-LSTM hybrid model achieved a detection accuracy of 96%, outperforming traditional machine learning classifiers. The false positive rate was significantly reduced, improving overall system reliability. Autoencoder-based models successfully detected previously unseen attacks, demonstrating strong anomaly detection capability.

Despite these advantages, challenges remain in deploying deep learning models in real-time environments due to computational overhead and the need for continuous model updates. Addressing data imbalance and ensuring explainability of model decisions are also critical for practical adoption.

7. Conclusion and Future Scope

Deep learning-based cybersecurity threat detection systems offer a powerful solution for protecting modern digital infrastructure. By learning complex patterns from network data, these systems can detect known and unknown attacks with high accuracy. Future research will focus on lightweight deep learning models for real-time deployment, explainable AI techniques for security transparency, and integration with automated response systems to enhance cyber resilience.

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